EXTERNALITIES IN THE MATCHING OF WORKERS AND FIRMS IN BRITAIN

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Abstract

We provide empirical evidence on the nature of spatial externalities in a matching model for the UK. We use a monthly panel of outflows, unemployment and vacancy stocks data from the registers at Jobcentres in the UK; these are mapped on to travel-to-work areas. We find evidence of significant spill-over effects that are generally in line with the predictions of theory. For example, we find that conditional on local labour market conditions, high unemployment levels in neighbouring areas raise the number of local filled vacancies but lower the local outflow from unemployment.

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1. Introduction

The matching approach is now one of the standard tools for analysing the labour market, but empirically at least is still largely a 'black box' approach. This paper provides empirical evidence for the UK on a relatively neglected aspect of matching: the importance of the externalities stressed by matching theory. The source of these spill-overs is easy to see in principle: one more vacancy influences the matching probability and hence decision problem of workers and other firms. These effects will not in general be internalised by wage setting, so market inefficiencies and the potential for multiple equilibria will remain.

Estimates of matching functions have been largely from aggregate time series[1], and spill-over effects are hard to get directly with such aggregate data. The focus in these papers is largely on looking at the estimated 'returns to scale'.[2] Recently, however, some authors have used cross-section or panel data[3], but with some exceptions have not really examined the externalities issue. Burda and Profit (1996) have extended the matching function to account for regional spill-overs from neighbouring regions on local employment probabilities. This paper applies their specification of the matching function to local labour markets in Britain, and extends their work, first, by exploring the effects on both unemployment and vacancy flows as dependent variables, and second, by analysing cyclical variations of spatial dependence in job-matching.

We look at small areas, in fact travel-to-work areas (TTWAs), and the influence of labour market conditions in the surrounding areas on matching probabilities. We use a monthly panel of unemployment and vacancy registration data at Jobcentres in the UK. The form of such spatial dependence is not clear from theory so we proceed cautiously, exploring the data in a fairly non-parametric way before specifying the form in a standard matching function format.

We find evidence of significant spill-over effects. For example, we find that conditional on local (TTWA) labour market conditions, high unemployment levels in neighbouring areas raise

[1] See for example, Pissarides (1986) and Blanchard and Diamond (1989). Other more recent examples are Berman (1997), Fox (1996), Gregg and Petrongolo (1997), Gross (1997), Warren (1996).
[2] Though see Anderson and Burgess (1995) for whether the sum of the coefficients can be so interpreted.
[3] See for example, Anderson and Burgess (1995), Burda and Profit (1996), Boeri and Burda (1996), Coles and Smith (1996), Münich, Svenjar and Terrell (1995).

the number of local filled vacancies but lower the local outflow from unemployment. High vacancy levels in neighbouring areas raise the local outflow from unemployment and the local outflow of filled vacancies. Interestingly, we also find cyclical variation in the degree of spatial dependence.

These results shed further light into the black box of the matching function. They show that one of the key matching function concepts, externalities, has empirical content. The rest of the paper is organised as follows: section 2 describes the data, section 3 sets out our exploratory analysis of the spatial dependence and section 4 presents the results of parameterising this in the standard specification of the matching function. Section 5 concludes.

2. Description of data and estimation of a benchmark matching function

The importance of understanding worker flows has proved to be an essential element in understanding the dynamic processes of labour markets (e.g. Blanchard and Diamond, 1989; Layard, et al., 1991; and Pissarides, 1986). We analyse monthly gross worker flows at a local level, estimating matching functions for 303 TTWAs in the UK between October 1985 and December 1995, as well as the interactions between them.[4] The geographic entities were originally constructed through an algorithm which ensures that at the time collecting the data a minimum of 75% of employed residents work within the district.[5] As such, travel-to-work areas constitute self-contained labour markets, which, at least at the time of construction, limit the role of migration and commuting on job-matching among regional entities. Hence, detecting significant spill-overs between TTWAs would indicate strong dynamics of regional change.

[4] Labour market data is extracted from NOMIS at University of Durham.

[5] TTWAs were constructed based on commuting data from the 1981 Census. The observations for February 1986 is missing. Four travel-to-work areas (Fishguard, Pickering and Helmsley, Ripon, Thirsk) contain a value of zero for vacancy stocks and vacancy outflows for most of the sample period. Since it is not clear whether these zero observations are due to misreporting, or to a revision of district borders, we decide to delete these districts. It turns out that the deletion of these districts changes the results dramatically. Moreover islands (Orkney, Shetland, Western Isles) with the exception of Isle of White, which is close enough to the mainland, and Northern Ireland were not considered in our analysis.

Unemployment and vacancy stocks and flows are registration data provided by local employment agencies. Such data has the advantage of being readily available on a regularly basis, at high frequencies, and at a very disaggregate regional level. On the other hand, such data suffers from well-known deficiencies: e.g. unemployment time series may be flawed by numerous redefinitions of the unemployment status over time, and the neglect of discouraged workers who have lost the incentive to register at Jobcentres.[6] Moreover, registered vacancies only constitute one channel from which firms recruit personnel and job-seekers find employment. Gregg and Wadsworth (1996) report for Britain, that about 70 percent of the unemployed, 30 percent of the employed and 50 percent of all employers use official Jobcentres as one of their search channels. Registered vacancies capture a disproportionate share of positions offered to low-skilled, manual workers as well as long-term unemployed, but account for only one third of total vacancies on average.[7] Furthermore, nothing can be said about the variation in non-registered vacancies across regions and over the business cycle. While Gregg and Wadsworth (1996) present evidence that the use of state employment services in Britain moves countercyclically, there is no evidence available on the spatial variation of search effort over the cycle.

Another important question concerns the choice of variables approximating the number of matches in travel-to-work areas over a certain time interval, i.e. one month. All available candidates suffer certain deficiencies. However, differences in their cyclical behaviour and their responsiveness to changes in unemployment and vacancies (both local and 'foreign') may shed light on certain aspects of the matching process in the UK. The first variable we use is unemployment outflows in district i over some period t: simply, the number of people leaving the unemployment register. Unemployment outflows have the clear drawback of including flows out of the labour force which can be expected to vary in size over the business cycle as well as across regions. Secondly, we use filled vacancies: vacancies notified in area i and filled

[6] One factor which mitigates the discouraged worker bias in the registration data is pointed out by Schmitt and Wadworth (1993). They find that, in contrast to common belief, workers who have lost eligibility for unemployment benefit search less intensively. Their explanation is that they are denied access to the training and counselling facilities of Jobcentres, underlining the important role of official employment agencies as a search channel in Britain.

[7] See Smith (1988), Green (1991), and Gregg and Wadsworth (1996).

during period t. Filled vacancies also include job finds due to activities of Career Offices, which mainly mediate school-leavers and labour market entrants (see Green, 1991). Figure 2 clarifies the accounting relationship between unemployment outflows and filled vacancies.[8] These are two different variables: they measure different events. So while in simple matching models they should be the same, because of employed job search, out-of-area hires, exits from the labour force and so on, there is no reason to expect them to behave the same empirically. Indeed, to the extent that they do have slightly different emphasis, this allows us to look at the impact on the two sides of the labour market separately.

A careful analysis of cross-section distributions of unemployment and vacancy outflow rates reveals considerable outlier problems in the data. For example, the maximum value of the ratio of filled vacancies over a month to the stock of vacancies at the beginning of the month takes a value of 22. Hence, we decided to replace the three largest and smallest observations in each travel-to-work area with a missing value, which amounts to about 5% of the sample.

The panel on the left hand side of Figure 1a shows total registered unemployment and vacancies between January 1986 and December 1995. As expected, unemployment moves countercyclically and vacancies procyclically, with either real GDP growth or employment growth as business cycle indicators (see right hand side panel in Figure 1b). Intensive research in recent years has provided clear evidence that aggregate employment inflows vary procyclically over the business cycle (see Antolin, 1995; Blanchard and Diamond, 1990; and Burda and Wyplosz, 1994). As the right panel of Figure 1a indicates, this is also true for the UK. The evidence on the cyclicality of unemployment outflows is less unambiguous. While Blanchard and Diamond (1990) and Burda and Wyplosz (1994) find countercyclical unemployment outflows for the US, France and Japan, Antolin (1995) and Gautier and Broersma (1994) show that unemployment outflows vary procyclically in Spain and the Netherlands. The right hand side panels of Figures 1a and 1b suggest that in Britain

[8] We also used data on job placings, which also include job seekers from i mediated to vacancies initially notified to other Jobcentres. However, the aggregate dynamics of this variable as well as regression results proved to be very similar implying that either mediations to other regions closely match with vacancies filled by Career Centres, or are negligible in size.

unemployment outflows seem to move countercyclically, following real GDP growth with a lag of more than one year.

Table 1a provides summary statistics for outflow rates for different levels of disaggregation. We consider both unemployment and vacancy flows of workers in the analysis on a regional level. Average unemployment outflow rates suggest a mean duration of an unemployment spell just above six months, whereas the average duration of vacancies is only slightly above one month. In Table 1b, travel-to-work areas are classified according to a region's degree of dependence on UK's principal urban centres ("metropolitan dominants"). Travel-to-work areas which were linked to the former by significant commuting ties are labelled "metropolitan subdominants". "Metropolitan rural areas" are also linked with commuting flows to one of the first two groups, but their main settlement falls below a certain threshold in size. Relatively independent areas are called "freestanding" and are divided in "urban" and "rural areas" according to the size of their main settlement.[9] Average unemployment outflow rates are lowest in metropolitan areas, particularly in London, which is, at least in part, due to the composition of the labour force with a larger proportion of high risk groups, i.e. young and ethnic minorities (see Fieldhouse, 1996). The impression of a stronger mismatch in metropolitan areas is supported by the a regional comparison of V/U ratios, which are the highest in London in Table 1c. But even when these compositional effects in the labour force are considered, the evidence of higher outflow rates in rural areas is striking, and may have inspired the acceleration of migration flows towards non-metropolitan areas during the 80s (see Champion, 1994). Disaggregating vacancy and unemployment flows by regions in Table 1c shows only weak evidence for a North-South divide on UK labour markets, widely discussed in the literature (see Martin, 1993).

As a first step in modelling, we consider a Cobb-Douglas specification of the matching function in log-linear form with fixed effects for time and districts,

$$\ln X_{it} = \mu_i + \eta_t + \alpha \ln U_{it-1} + \beta \ln V_{it-1} + u_{it} ,$$

[9] The classification is taken from a framework of local labour-market areas (LLMA) devised by the Centre for Urban and Regional Studies at Newcastle University to analyse urban and regional change (see Coombes, 1982). We match the 281 LLMAs with 310 TTWAs to transfer the classification. See also Champion (1994).

where X_{it} is the number of matches in area *i* during month *t* (we use separately the number of vacancies filled through official jobcentres in the same district, and the number of outflows from unemployment), U_{it-1} and V_{it-1} are stocks of registered unemployed and vacancies in area *i* at the beginning of period *t*. μ_i is an area fixed effect controlling for regional characteristics and size of an area, η_t is a time fixed effect controlling for an aggregate time trend as well as seasonal fluctuations of worker-firm matches, and u_{it} is an error term for which the usual properties apply.

To avoid simultaneity bias in the estimation of the matching function for Britain, we regress the number of job-matches during a month on unemployment and vacancy stocks at the beginning of the month. However, Jobcentres count unfilled vacancies on the first Friday, whereas unemployment counts are on the second Thursday of each month. Therefore, even when we use lagged unemployment in the *filled vacancy* regression, there exists a period of overlap of four to nine workdays, which may give rise to a simultaneity bias. This may potentially produce a downward in the estimated elasticity of filled vacancies with respect to unemployment. No problem arises if unemployment outflows are used as dependent variable. A possible remedy of the simultaneity problem is to instrument unemployment stocks with higher order lags of the same variable. Since instrumental variable regressions produced qualitatively similar results (not reported), we report simple OLS results in what follows.

We begin with estimating simple OLS pooling over all districts between October 1985 and December 1995 in Table 2, restricting μ_i and η_t to be constant across areas and time. Looking first at filled vacancies as the dependent variable, we find positive and significant coefficients of unemployment and vacancy stocks as expected from the theory of job-matching, with the coefficient of vacancies being more than twice as high as the one on unemployment.[10] Returns to scale are close to one, but are statistically rejected in favour of decreasing returns. However, with unemployment outflow as the dependent variable the coefficient on unemployment is just above 0.75, more than four times larger than that on vacancies.

[10] This result closely resembles the findings of Coles and Smith (1996).

To account for structural heterogeneity among the TTWAs (not least the fact that the TTWAs vary considerably in size) as well as common aggregate factors, we allow for regional and time fixed effects in our empirical model. Adding only time fixed effects, or seasonal effects and time trends only marginally changes the coefficients on unemployment and vacancy stocks compared to regression (1), though the variables are highly statistically significant. This implies that aggregate conditions do not matter much for the stock-flow relationship on local labour markets, conditional on the local unemployment and vacancy stocks.

However, adding TTWA fixed effects to the model drastically changes the results. With unemployment outflows as the dependent variable, the coefficients on log unemployment and vacancies drop significantly, compared to regression (1), but remain positive and significant. This result confirms the findings of Bennett and Pinto (1994) who also examine hiring functions for the UK at a regional level for a similar period of time. However, they find a larger elasticity of hires with respect to vacancies. The difference in results probably arises from the lower level of regional disaggregation as well as differences in the choice of the dependent variable in Bennett and Pinto (1994).[11] The matching function clearly indicates decreasing returns to scale. However, using filled vacancies, the coefficient on unemployment drops sharply and becomes negative when both time and district fixed effects are considered. Hence, the positive relation between unemployment stocks and vacancy flows in the pooled regressions found by Coles and Smith (1996) and Bennett and Pinto (1994) may be a pure scale effect due to the size of travel-to-work areas. Regressions in column (3) present a more parsimonious specification with district fixed effect but seasonal dummies and linear, quadratic and cubic time trends rather than time fixed effects for each period; the results remain largely unchanged.[12]

High t-values in regressions (1) - (3) may indicate potential problems with residual autocorrelation and/or heteroscedasticity. Diagnostic tests (LM test for groupwise heteroscedasticity and a Durbin-Watson test for serial correlation)[13] clearly support this

[11] Bennett and Pinto (1994) have used unemployment-to-job transitions as a proxy of job-matches.
[12] If we use regional instead of TTWA fixed effects, as in Table 6, the coefficient on unemployment becomes unambiguously positive, which implies a strong correlation between district fixed effects and unemployment.
[13] A Breusch-Godfrey tests (not reported) also indicates the presence of higher order serial correlation.

impression. We apply a three-stage *GLS* procedure to account for non-spherical disturbances: (a) an LSDV model is estimated with OLS to obtain a consistent estimator of the autocorrelation function. (b) The transformed model is estimated taking into account serial correlation in job matches. For monthly data, estimating an AR(12) process seems reasonable. Table 3 shows that the autoregressive coefficients are highly significant for both dependent variables. (c) residuals from (b) are used to consistently estimate area-specific variances for all TTWAs by weighted least squares. We choose two variants in step (a): first, the AR(12) function is restricted to be equal across travel-to-work areas, and all three steps are estimated using time and area fixed effects. Second, the autocorrelation function is allowed to vary across travel-to-work areas, and is estimated for each cross-section separately. In this variant, only seasonal fixed effects and time trends are included in step (a) of the estimation procedure.

The results are shown in regressions (4) and (5). When filled vacancies or placings are taken as a proxy of matches and the AR(12) process is restricted to be equal for all cross-sections, the coefficient on unemployment becomes positive but insignificant, whereas an increase in the stock of vacancies still has a positive effect on the number of job-matches. For unemployment outflows, the coefficient on unemployment remains roughly unchanged whereas the coefficient on vacancies becomes much smaller, compared to (2) and (3). When we allow for varying autoregressive processes across travel-to-work areas, regression (5), the coefficients on unemployment in the *filled vacancy* regression becomes significantly positive, which reconciles our results with standard matching theory, although the coefficient is still very small. Even after accounting for groupwise heteroscedasticity and autocorrelation, t-values, especially for the coefficient on unemployment in the regression (4) and (5) remain very high. This may indicate the presence of heteroscedasticity of unknown form within TTWAs.

The regression results in Table 2 show, that after considering the impact of the deficiencies of available proxy variables for job-matches, and acknowledging the problems with labour market stock variables expressing the *true* degree of labour market tightness, the matching function seems to hold even on a local scale. However, Burda and Profit (1996) have demonstrated that this formulation of the matching function may be misspecified when spatial spill-over effects in local labour markets are present. Job-search activities of workers and recruiting activities of firms across district borders may influence the job-matching process in neighbouring regions.

3. Spatial Dependence

None of the matching function estimates in Table 2 consider the possibility that labour market stocks have an impact on flow variables in adjacent TTWAs. If regional interdependencies are present in local labour markets, such matching functions may be misspecified (see Anselin, 1988). Measuring the strength and average sign of interaction effects across districts can explain the dynamics of regional mobility of workers without assessing migration and commuting patterns directly. Although TTWAs in the UK were constructed to minimise commuting flows, search behaviour can clearly range more widely, (also mobility patterns may have changed during the 80s and early 90s) and hence interaction effects may constitute an important component of local job-matches. In addition, viewing local labour market dynamics from an indirect angle may even be a superior approach, since prevailing migration and commuting patterns only constitute the outcome of the search process, whereas spatial spill-overs measured in the matching function also capture the impact of the search effort of labour market participants targeting adjacent regions. Finally, Anselin (1988) has shown that considering the regional dimension explicitly may also be justified on pure econometric reasons, since omitting spatial interaction effects may produce biased and inconsistent estimates.

An informal test whether spatial effects are present among local labour markets in Britain is obtained by exploring the relation between the residual correlation from the matching function (4) in Table 2 and road distances between main settlements within each of the TTWAs.[14] Figure 3a and 3b demonstrate that while road distances between districts only explain a small part of the residual correlation, they have a significant negative impact on

[14] Road distances are measured to yield the fastest connection between the main settlements of two TTWAs, and calculated from the software *Milemaster Home* of the *UK Automobile Association*. Instead of filling all cells in the 303×303 distance weighting matrix, only pairs of TTWAs up to fifth order contiguity were taken into account. In the latter analysis, only external effects from TTWAs within 120 km were assumed to be relevant.

residual correlation for both dependent variables. This distance decay effect is consistent with diminishing search intensities due to higher costs of job-search at longer distances, and therefore reduced spatial spill-overs between TTWAs at longer distances. Table 4 presents the result of a regression of residual correlations on log distance, different orders of contiguity and regional fixed effects. The reported specifications were selected according to AIC. The residual correlation falls significantly as log distance increases, even after controlling for the degree of contiguity and a large sets of regional dummies. Moreover, residual correlation declines with higher order contiguity. Fixed effects reveal a strong residual correlation among TTWAs in the London region, and high positive residual correlation between London TTWAs and those in the South East region. In particular, for unemployment outflows, Table 4 indicates significant negative interaction effects between TTWAs from northern regions. Summing up, spatial correlation seems to be more pronounced in the matching function with unemployment outflows as a dependent variable, where spatial variables explain an extra 12 percent of residual correlation.

A more formal way of testing for spatial dependence is to use Moran's *I* test (see Anselin and Hudak, 1992). This test is designed to detect spatial correlation from cross-section regression residuals. We adapt Moran's *I* test to a regional panel, taking the residual of the pooled regression (4) in Table 2, and calculate the test statistic for each cross-section separately. The test statistic for each period *t* is constructed as

$$MI_t = \frac{u_{it}' W u_{it} / \omega}{u_{it}' u_{it} / N},$$

where u_{it} is the regression residual, W is the $N \times N$ weight matrix, which, in our case, either contains some measure of road distances, or first-order contiguity dummies for each pair of TTWAs (the latter matrix contains a value of one, if two districts share a common border). In the context of job-matching, the absolute size of spatial spill-over effects is of interest, hence no row-standardisation was applied to weighting matrixes. ω is the sum of all elements of the respective weighting matrix, and N is the number of TTWAs. The test statistic is standardised to follow asymptotically a normal distribution (Anselin and Hudak, 1992). Figure 4 shows the values of the z-statistics of Moran's *I* based on matching function residuals for worker flows, Figure 4a, and unemployment flows, Figure 4b, during the whole sample period. Left hand side panels use a first-order contiguity matrix, whereas right hand side panels incorporate a distance weighting matrix. Following Mohlo (1995), we specify an exponential distance function as $\omega_{ij} = \exp\left(-\eta D_{ij}\right)$, where η = 0.02 and ω_{ij} is one element of the distance weighting matrix *W*.[15] The upper panels in each figure use plain regression residuals to calculate Moran's *I*. Since an important part of spatial effects may be captured by district and time specific constants in the empirical matching function, the bottom panels add time and TTWA fixed effects to the regression residual. All figures indicate strong seasonal effects and random movements in the test statistic over time. Solid lines show a 12-month's moving average and reveal significant spatial dependence during the whole sample period. For *plain* residuals of the matching function with filled vacancies, Moran's *I* indicates declining spatial dependence, whereas spatial dependence increases in the '90s, when we consider *fixed effects augmented* residuals. A very similar pattern emerges from Figure 4b. As expected, spatial dependence seems to be much more pronounced in the *augmented residual* case.

Worker-flow studies have intensively discussed the cyclicality of these variables and the underlying economic processes.[16] A stylised fact which arises from these studies is that worker flows move procyclically, while the cyclical behaviour of unemployment flows differs across countries. Surprisingly, the regional dimension has been not been approached so far, probably due to the lack of sufficiently disaggregated data. Cyclical movements of regional spill-overs in job-matching can be justified through variations in individual search effort, varying intensity of use of search and recruitment channels and compositional effects. First, spatial search costs, as well as job finding probabilities may vary through booms and recessions, and induce different individual search efforts across regions. Second, Gregg and Wadsworth (1996) have provided evidence that the intensity of use of certain search and recruitment channels varies with the

[15] The value of η is set a value of 0.02 according Mohlo (1995) who analyses the impact of the accessibility of a region on the level of unemployment in Britain. Let alone, road distance is a very crude, yet the best available measure for search costs. However, in order to account for the quality of e.g. infrastructure, geographic accessibility η should be a function of these variables.

[16] See Burda and Wyplosz (1994) or Mortensen (1994) for a summary of stylised facts.

cycle. Assuming that different search channels have a different regional impact, it is clear that a labour market participant's choice of search and recruitment channels also determines the degree to which her search effort reaches out across space. Finally, the composition of the pool of job seekers may not be invariant over the cycle: in economic downturns, labour shedding is more likely to affect all types of workers, whereas inflows into the unemployment pool during booms is more likely to be of a selective nature. Moreover, employed job-search is procyclical.[17] If different types of job seekers vary with respect to search intensities and search methods, it is plausible to expect that also spatial search behaviour varies with the business cycle.

Figures 4a and 4b indicate that, similar to their levels, the strength of spatial dependencies of filled vacancy and unemployment flows fluctuates in opposite directions, even after controlling for the number of unemployed and vacancies in a local labour market. The intensity of spatial correlation for unemployment outflows moves countercyclically, and procyclically for vacancy flows, both lagging one year behind real GDP growth. This patterns becomes evident in the following regressions, which use moving averages of Moran's *I* statistics as displayed in the upper right panel of Figures 4a and 4b transformed to quarterly observations to match with data on real GDP growth as shown in Figure 1b,[18]

$$\underset{}{z\left(MI^{uo}\right)_t} = \underset{(3.93)}{2.750} + \underset{(1.06)}{0.017}\ time + \underset{(8.41)}{0.607}\ z\left(MI^{uo}\right)_{t-4} - \underset{(2.39)}{0.157}\ \Delta \ln GDP_{t-4} + \varepsilon_t^{uo}$$

$$z\left(MI^{vf}\right)_t = \underset{(0.99)}{0.467} + \underset{(0.15)}{0.002}\ time + \underset{(8.21)}{0.806}\ z\left(MI^{vf}\right)_{t-4} + \underset{(1.98)}{0.107}\ \Delta \ln GDP_{t-4} + \varepsilon_t^{vf}$$

An increase in lagged real GDP by one percent depresses Moran's I statistic in the case of *unemployment outflows* by 0.16, whereas it increases by 0.11 in the case of *filled vacancies*. This seems to make sense: in good times, the unemployed lower their search radius, but

[17] See Gregg and Wadsworth (1996). For an analysis of on-the-job search on unemployed job seekers, see Burgess (1993).

[18] Absolute t-values given in parentheses. Number of observations is 29, adjusted R^2 is 0.84 in the first regression and 0.79 in the second. $z(MI^{uo})$ is the moving average of the standardised Moran *I* statistic (based on plain residuals) from the regression with unemployment outflows as the dependent variable, $z(MI^{vf})$ is the corresponding test statistic for the filled vacancy regression.

emnployers are forced to increase theirs; in bad times, the unemployed have to search more widely, but firms can afford to search more locally. The finding for cyclical movements in spatial dependence for the residual of the UK matching function with unemployment outflows as dependent variable is similar to the finding of Gregg and Wadsworth (1996) that in booms, job-seekers use fewer search methods.

4. Estimation of Spatial Spill-overs

Testing for spatial dependence in the previous section provides strong evidence for the existence of regional spill-overs in local job-matching in Britain. For travel-to-work areas designed to minimise commuting and migration flows among them, suggests that job searchers look further afiled than their local commuting area (or that regional mobility patterns have changed in the UK since 1981).

We now investigate this spatial dependence more sytematically. Burda and Profit (1996) have presented a stylised model of non-sequential job search, where job seekers optimise individual search intensities across local labour markets trading-off expected benefit of job-search against its costs. Both of these are assumed to depend on the distance between residence and target regions. Optimal search and recruiting intensities determine the relevant pools of participants in a local labour market. Plugging optimal search intensities into a generalised matching function which relates job-matches to economic conditions everywhere, reveals that *(a)* changes in unemployment exit probabilities in a district *i* are linked to changes in local labour market conditions in any district *j* through a complex function of the effect on exit probabilities in all other districts. *(b)* the size and sign of external effects depend on a weighted sum of the impact on changes of exit probabilities in all other districts, where the weights are determined by a direct effect of the change of local labour market conditions elsewhere, plus an indirect effect which arises from changing search intensities in other districts. Burda and Profit (1996) estimate a linear approximation of this *augmented* matching function of the following form,

$$\ln X_{it} = \mu_i + \eta_t + \alpha \ln U_{it-1} + \beta \ln V_{it-1} + \mathrm{a}^* \ \ln \mathrm{U}^*_{it-1} + \mathrm{b}^* \ \ln \mathrm{V}^*_{it-1} + u_{it} \, ,$$

where vectors U_{it-1}^{*} and V_{it-1}^{*} measure external effects of unemployment and vacancies in *foreign* travel-to-work areas, and a* and b* the respective row vectors of coefficients.

Spatial spill-overs estimated and presented in Table 5 and 6 are specified, first, by a distance weighted sum of the number of unemployed and vacancies, WU_{t-1} and WV_{t-1}, where, as before, W is the $N\times N$ distance weighting matrix with elements $\omega_{ij} = \exp\left(-\eta D_{ij}\right)$, and η = 0.02, $i\neq j$, and $i,j\in\{1,...,N\}$. The distance decay function suggests a weaker impact of *foreign* districts on local labour markets as suggested by Burda and Profit (1996), since search costs rise at larger distances and search intensities diminish. A second specification only considers spatial spill-overs from contiguous districts applying a first order contiguity matrix W^c. Finally, we address the possibility of non-uniform spatial dependence at varying distances by adding unemployed and vacancies within certain ranges of distance from each travel-to-work area. Since no other weighing scheme is applied here, coefficients should, according to the *spatially augmented* matching function, diminish with growing distance.

Table 5 shows results using both unemployment exits and filled vacancies as dependent variables, and including external unemployment and vacancies as described above. Regressions (1) and (4) consider local labour market conditions in contiguous TTWAs, in regressions (2) and (5) distance weighted labour market stocks are compounded into a single index, and (3) and (6) augment the matching function with external unemployment and vacancies within certain ranges of distance.

As before, the elasticity of unemployment outflows with respect to unemployment and vacancies is positive and significant. However, we find a strong negative congestion effect of higher unemployment in other travel-to-work areas. This finding is robust across all specifications, and regression (3) shows that the externality is strongest for the numbers unemployed found in a range between 30 and 60 kilometres. The negative externality of foreign unemployment probably reflects strong competition for vacancies in a TTWA from neighbouring TTWAs. Unemployed workers contacting a ‘foreign’ Jobcentre in another district can be expected to exhibit a higher total search intensity on average compared to the local unemployment pool. For vacancies, the externality is unambiguously positive and significant, with an elasticity that is higher compared to the effect of a change of local vacancies. Again, the elasticity of unemployment outflows with respect to external vacancies is the strongest for TTWAs within 30 to 60 kilometres distance. Even with accounting for spatial spill-overs, the UK matching function clearly exhibits decreasing returns-to-scale in all tested specifications.

When filled vacancies are used to proxy job-matches, we found a negative and significant elasticity with respect to local unemployment. However, results more in keeping with standard matching theory are recovered when spatial spill-over effects are taken into account. The strong positive externality of unemployed from other travel-to-work areas -- again the effect is strongest for unemployed from TTWAs within a range from 30 to 60 kilometres -- indicates that UK Jobcentres are very successful in mediating local vacancies to job seekers from other districts, and that job seekers exhibit the flexibility to accept these jobs.[19] Another interpretation of the strong positive external effect of *foreign* unemployment is due to the fact that filled vacancies only count matches accruing from one search channel, e.g. official Jobcentres. Since, *at home*, job seekers attain local labour market information at lower costs, it seems reasonable to assume that the diversification of search channels is higher compared to job seekers from other regions, who will probably rely on the official employment service.

A comparison of tests for spatial dependence based on plain residuals and residuals plus fixed effects, Figures 4a and 4b, shows that fixed effects capture a considerable part of spatial spill-overs. Therefore we estimate a more parsimonious specification of the spatially augmented matching function for Britain in Table 6, with controls for regional instead of TTWA fixed effects. In addition, a set of basic characteristics of local labour markets is included to capture the heterogeneity among districts. Since coastal districts are less accessible, we expect them to exhibit a smaller matching efficiency *a priori*. Infrastructure is approximated by a set of dummy variables, which feature the degree of dependence on principal urban

[19] It is important to remember that filled vacancies are defined as counting positions notified to a local employment service and filled with a job seeker referred to any Jobcentre or other agencies to whom it has copied the vacant position.

centres in Britain.[20] Finally, we add a dummy variable which takes the value one if the TTWA is crossed by a motorway. Since job-related mobility costs should be smaller in such districts, we expect them to have a higher matching efficiency.

In the regressions with log unemployment outflows as a dependent variable, (1) to (3), controlling for regional fixed effects and a set of structural dummies in Table 6 does not alter the results concerning the matching coefficients of local and *foreign* unemployment and vacancies, although returns to scale are much closer to one. However, a T-test still rejects *CRTS*. Dummies which characterise the relationship to principal urban centres are largely insignificant. As expected the matching efficiency of coastal districts is lower, whereas districts which are crossed by motorways exhibit a higher matching efficiency. When matches are approximated by filled vacancies, regressions (4) to (6), and regional fixed effects are used instead of district fixed effects, the coefficient on unemployment increases to about 0.36, while the elasticity with respect to external unemployment on local matching becomes negative. It follows that the TTWA fixed effects in regressions (4) to (6) in Table 5 capture the negative externality of foreign unemployment. The matching efficiency in predominantly metropolitan areas is significantly higher than in the districts surrounding them. TTWAs which have direct access to motorways again have a higher matching efficiency, though the positive effect of the dummy for coastal districts is a surprising result.

All regressions and specifications indicate that external effects of unemployment and vacancies play an important role for the matching process in a local labour market. The findings underline the importance of the regional dimension to an understanding of labour market flows.

5. Conclusions

In this paper we have provided empirical evidence on the nature of spatial externalities in a matching model for the UK. We find evidence of significant spill-over effects. These are generally, though not universally, in line with the predictions of theory. For example, we find

[20] See Table 1b and the respective description in the text.

that conditional on local (TTWA) labour market conditions, high unemployment levels in neighbouring areas raise the number of local filled vacancies but lower the local outflow from unemployment. High vacancy levels in neighbouring areas raise the local outflow from unemployment and the local outflow of filled vacancies. Some of these results are robust across a variety of specifications, some are more sensitive.

A number of empirical puzzles[21] in this data remain for further investigation but overall, the results are supportive of the matching approach and show that one of the key matching function concepts, externalities, has empirical content.

[21] The different behaviour of the two dependent variables is a prime topic we wish to investigate.

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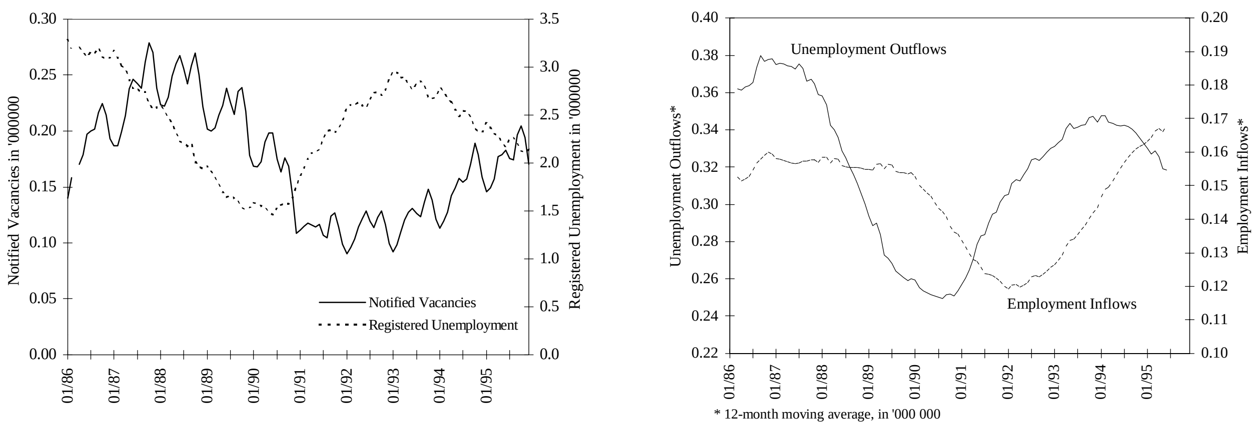


Figure 1a. Registered unemployment and vacancies, unemployment outflows and filled vacancies, *Source*: NOMIS/DE

Figure 1b. Aggregate unemployment, employment and real GDP growth rates, *Sources:* OECD standardised unemployment rates, Labour Force Statistics, OECD Economic Outlook, various issues.

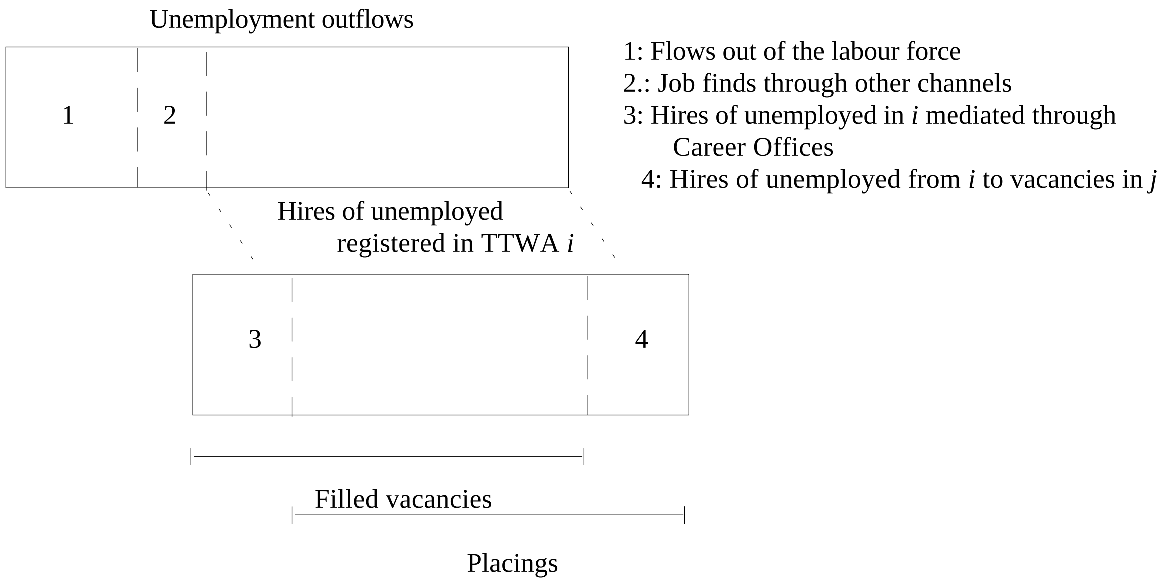


Figure 2. Gross employment and unemployment flows

Figure 3a. Residual correlation and distance, dependent variable: log filled vacancies

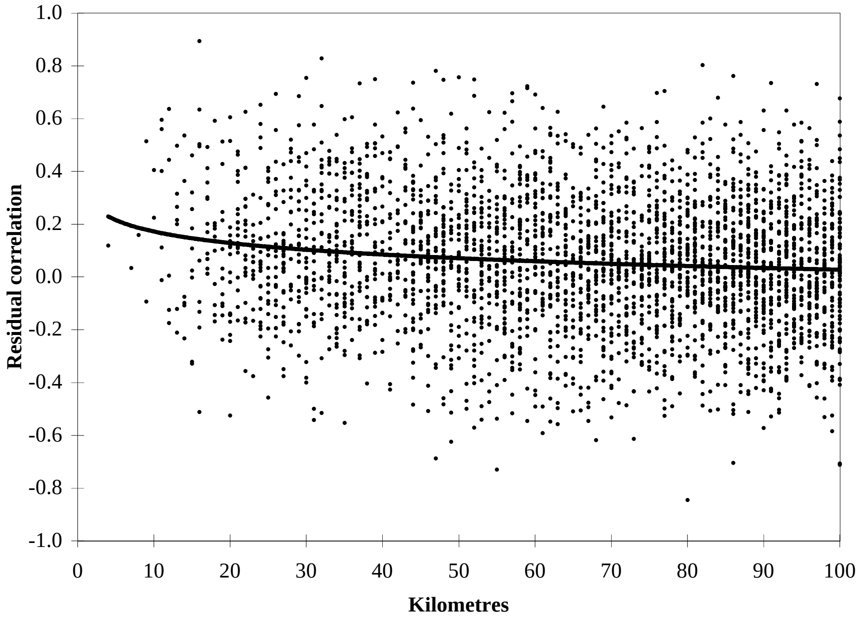


Figure 3b. Residual correlation and distance, dependent variable: log filled vacancies

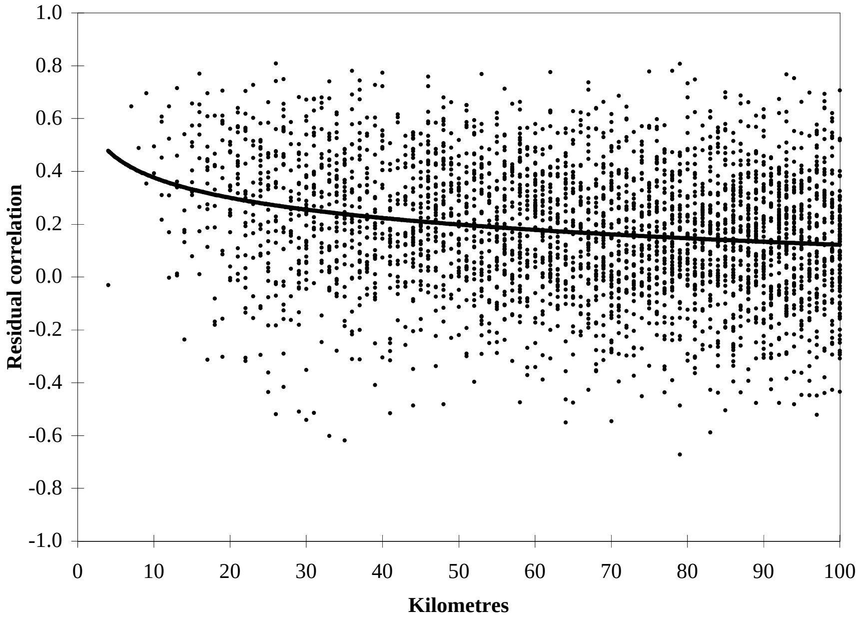
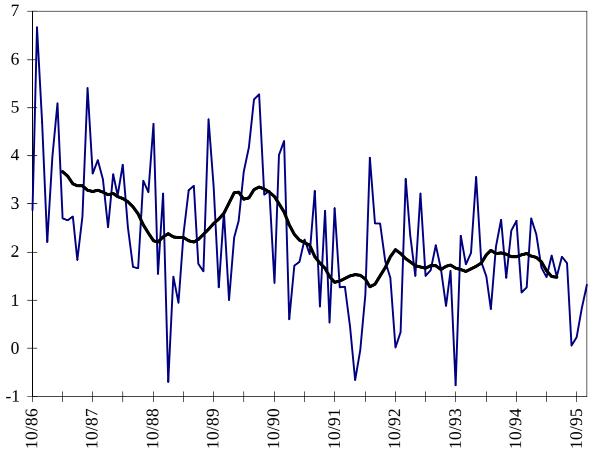


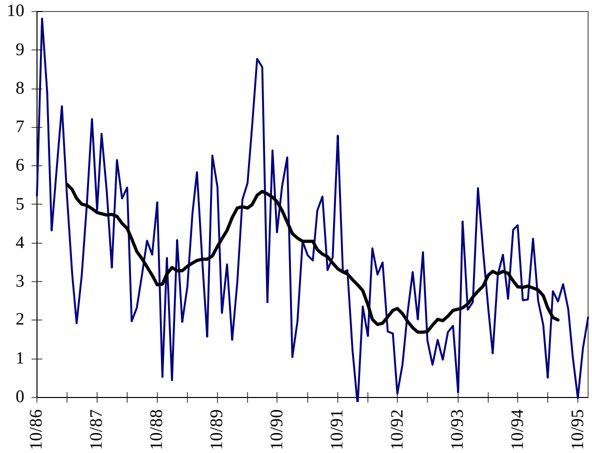
Figure 4a. Moran's I (z-statistics) for spatial dependence of residuals of matching function with filled vacancies, (12-month moving averages)

-- *plain residuals without fixed effects* --

1st order contiguity

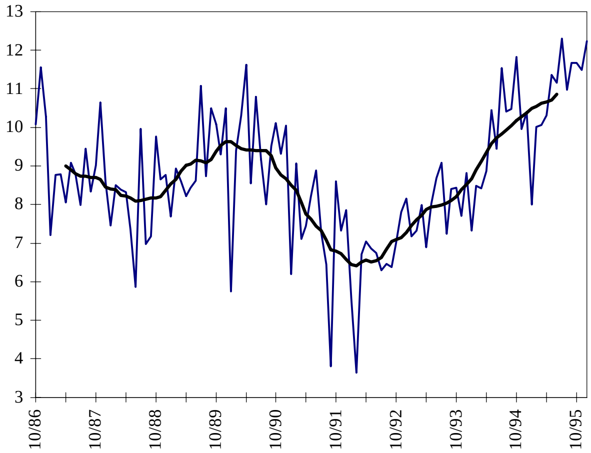


distance, η=0.02



-- *residual plus fixed effects* --

1st order contiguity



distance, η=0.02

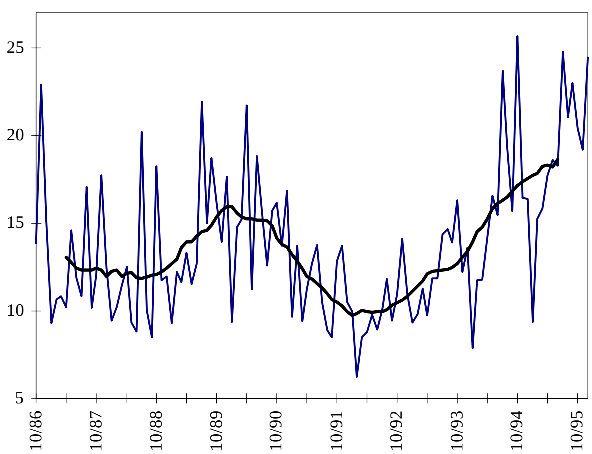
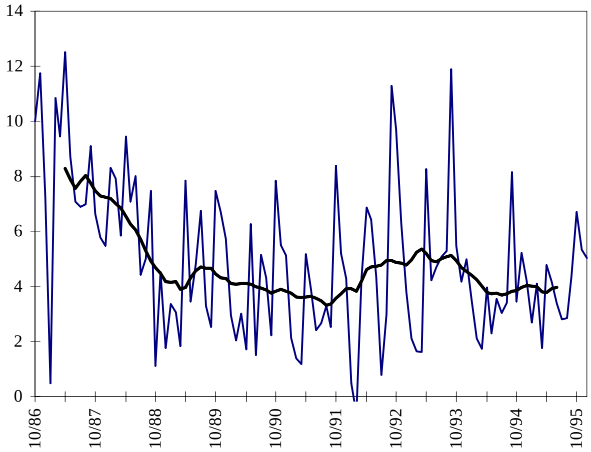


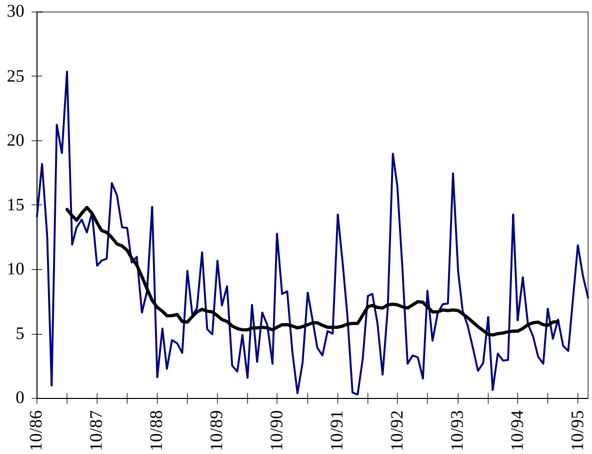
Figure 4b. Moran I (z-statistics) for spatial dependence of residuals of matching function with unemployment outflows, 2-month moving averages)

-- plain residual without fixed effects --

1st order contiguity

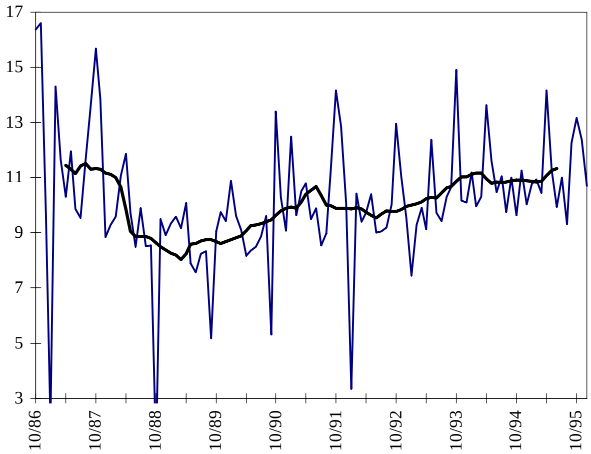


distance, η=0.02



-- residual plus fixed effects --

1st order contiguity



distance, η=0.02

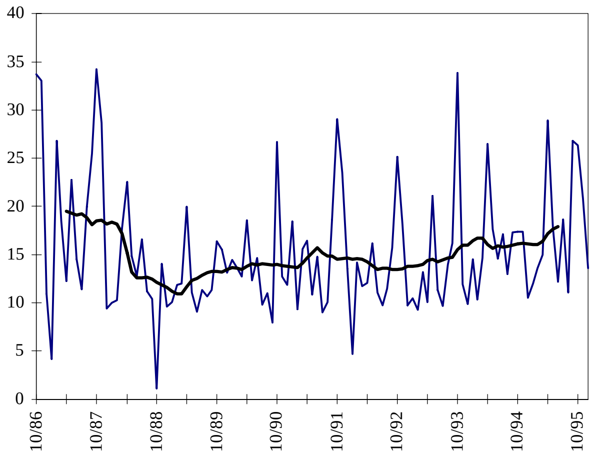


Table 1a. Unemployment and vacancy outflow rates and V/U ratio, 303 travel-to-work areas, Sept 1985-Dec 1995

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
UO_t/U_{t-1}	34845	0.160	0.045	0.058	0.421	0.897	1.289
VF_t/V_{t-1}	34845	0.934	0.429	0.048	8.831	1.994	15.805
V_{t-1}/U_{t-1}	36966	0.695	0.091	0.172	1.211	0.049	1.083

Table 1b. Unemployment and vacancy outflow rates and V/U ratio by type of district

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
UO_t/U_{t-1}							
- metropol. dominant	3220	0.142	0.043	0.059	0.336	1.118	1.651
- metropol. subdom.	7015	0.153	0.042	0.064	0.340	0.885	0.985
- metropol. rural	1495	0.171	0.048	0.069	0.405	1.097	2.142
- freestanding urban	17480	0.162	0.044	0.058	0.421	0.954	1.682
- freestanding rural	8625	0.167	0.046	0.058	0.375	0.615	0.320

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
VF_t/V_{t-1}							
- metropol. dominant	3220	0.951	0.366	0.108	2.599	0.748	0.635
- metropol. subdom.	7015	0.936	0.399	0.123	2.957	0.741	1.132
- metropol. rural	1495	0.917	0.402	0.116	3.933	1.990	7.954
- freestanding urban	17480	0.934	0.415	0.059	4.524	1.278	3.453
- freestanding rural	8625	0.910	0.487	0.048	8.831	3.432	33.950

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
V_{t-1}/U_{t-1}							
- metropol. dominant	3388	0.723	0.073	0.369	1.006	0.146	1.247
- metropol. subdom.	7381	0.715	0.085	0.408	1.020	0.408	0.516
- metropol. rural	1573	0.689	0.074	0.369	0.925	-0.382	0.617
- freestanding urban	18392	0.698	0.092	0.234	1.211	0.086	1.168
- freestanding rural	9075	0.680	0.100	0.172	1.172	0.060	0.671

Table 1c. Unemployment and vacancy outflow rates and V/U ratio by region

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
UO_t/U_{t-1}							
South East	4485	0.171	0.049	0.069	0.419	0.868	0.994
East Anglia	2185	0.172	0.041	0.081	0.314	0.512	-0.100
London	230	0.139	0.037	0.078	0.238	0.563	-0.320
South West	5520	0.168	0.043	0.067	0.396	0.813	1.006
West Midlands	2530	0.151	0.041	0.067	0.340	0.644	0.404
East Midlands	3105	0.160	0.045	0.068	0.343	0.816	0.678
Yorks.and Humberside	2760	0.156	0.041	0.066	0.334	0.768	0.660
North West	2300	0.154	0.042	0.059	0.336	0.773	0.942
Cumbria	805	0.179	0.064	0.077	0.421	1.166	1.167
Northern	1495	0.141	0.034	0.066	0.312	1.031	1.956
Wales	3795	0.150	0.039	0.064	0.336	0.839	0.975
Scotland	5635	0.158	0.047	0.058	0.405	0.935	1.493

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
VF_t/V_{t-1}							
South East	4485	0.691	0.319	0.123	2.833	1.215	2.589
East Anglia	2185	0.952	0.424	0.271	3.143	0.900	0.700
London	230	0.902	0.466	0.256	2.096	0.840	-0.392
South West	5520	0.918	0.412	0.150	6.729	2.075	12.798
West Midlands	2530	0.926	0.368	0.224	2.500	0.554	0.016
East Midlands	3105	0.999	0.383	0.233	3.134	1.063	1.873
Yorks. Humberside	2760	1.027	0.357	0.297	3.013	0.927	1.709
North West	2300	1.230	0.415	0.335	3.826	1.266	4.488
Cumbria	805	1.127	0.493	0.305	3.255	1.304	2.356
Northern	1495	1.128	0.444	0.282	3.500	1.132	1.880
Wales	3795	0.878	0.525	0.048	8.831	5.098	52.809
Scotland	5635	0.899	0.393	0.108	3.933	1.380	4.599

	N	Mean	StDev	Min	Max	Skewness	Kurtosis
V_{t-1}/ U_{t-1}							
South East	4758	0.746	0.102	0.378	1.170	0.243	0.227
East Anglia	2318	0.692	0.102	0.362	0.966	0.219	-0.326
London	244	0.781	0.062	0.675	0.903	0.130	-1.037
South West	5856	0.681	0.097	0.301	0.989	-0.283	0.312
West Midlands	2684	0.699	0.077	0.446	0.943	0.021	-0.121
East Midlands	3294	0.686	0.077	0.299	0.909	0.003	0.250
Yorks. and Humberside	2928	0.673	0.070	0.369	0.938	0.413	1.149
North West	2440	0.724	0.057	0.559	0.946	0.273	0.303
Cumbria	854	0.716	0.107	0.511	1.211	1.281	2.188
Northern	1586	0.661	0.0625	0.408	0.823	-0.757	0.832
Wales	4026	0.694	0.084	0.218	1.172	-0.174	2.719
Scotland	5978	0.677	0.095	0.172	1.039	-0.394	0.798

Table 2. Estimating Matching Functions
Sample: October 1985-December 1995, 303 travel-to-work areas, 121 periods.

		OLS	LSDV		GLSDV	
Dependent variable (in logs)	*Explanatory variables (in logs)*		*district and time fixed effects*	*district fixed effects, seasonal dummies and time trend*	*district and time fixed effects, uniform AR(12) and groupwise heterosced.*	*district and time fixed effects, distr.-spec AR(12) and groupwise heterosced.*
		(1)	*(2)*	*(3)*	*(4)*	*(5)*
Filled vacancies, t						
	Unempl., t-1	0.290*	-0.014	-0.020*	0.008	0.028*
		(0.003)	(0.009)	(0.007)	(0.015)	(0.006)
	Vacancies, t-1	0.682*	0.445*	0.457*	0.450*	0.427*
		(0.003)	(0.005)	(0.005)	(0.006)	(0.004)
	$\text{time} \times 10^{-2}$	--	--	-0.143*	--	--
				(0.060)		
	$\text{time}^2 \times 10^{-5}$	--	--	-0.348	--	--
				(0.116)		
	$\text{time}^3 \times 10^{-5}$	--	--	0.021*	--	--
				(0.005)		
	adj. Rsq.	0.89	0.95	0.94		
	RTS	0.972	0.431	0.437	0.458	0.455
		(225*)	(2371*)	(3627*)	(977*)	(4036*)
	DW	0.79	1.18	1.34	1.94	--
	N	34845	34845	34845	32045	32045
Unemploy. outflows, t						
	Unempl., t-1	0.776*	0.640*	0.639*	0.666*	0.605*
		(0.002)	(0.004)	(0.004)	(0.006)	(0.003)
	Vacancies, t-1	0.187*	0.068*	0.069*	0.035*	0.063*
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	$\text{time} \times 10^{-2}$	--	--	3.775*	--	--
				(0.255)		
	$\text{time}^2 \times 10^{-2}$	--	--	0.584*	--	--
				(0.033)		
	$\text{time}^3 \times 10^{-2}$	--	--	-0.012*	--	--
				(0.001)		
	adj. Rsq.	0.97	0.99	0.98	0.99	0.99
	RTS	0.963	0.708	0.708	0.701	0.668
		(1366*)	(3432*)	(3260*)	(2188*)	(7618*)
	DW	1.33	1.33	2.04	1.95	--
	N	34845	34845	34845	32154	32154

Keys: Standard errors in parentheses below coefficients. Due to the large number of observations, we only interpret coefficients at 1% significance, labelled with an asterisk. The number in parentheses below *RTS* gives the result of the T-test for *H0:CRTS*.

Table 3. Estimates of autoregressive parameters AR(12) for matching functions with time and district fixed effects

Dependent variable: log filled vacancies

Lag	Coefficient	Std Error	t Ratio
1	-0.251	0.0055	-45.17
2	-0.132	0.0057	-23.14
3	-0.079	0.0058	-13.69
4	-0.037	0.0058	-6.45
5	-0.030	0.0058	-5.21
6	-0.005	0.0058	-0.80
7	-0.006	0.0058	-1.06
8	0.004	0.0058	0.71
9	-0.014	0.0058	-2.48
10	-0.032	0.0058	-5.58
11	-0.029	0.0057	-5.03
12	-0.166	0.0055	-29.84

Dependent variable: log unemployment outflows

Lag	Coefficient	Std Error	t Ratio
1	-0.208	0.0053	-38.75
2	-0.107	0.0055	-19.57
3	-0.032	0.0055	-5.76
4	-0.004	0.0055	-0.80
5	0.018	0.0055	3.21
6	0.041	0.0055	7.37
7	0.005	0.0055	0.92
8	0.019	0.0055	3.42
9	-0.034	0.0055	-6.11
10	-0.053	0.0055	-9.59
11	-0.061	0.0055	-11.09
12	-0.291	0.0054	-54.21

Table 4. Residual correlation and distance

	Dependent variable	
	log filled vacancies	log unemploy. outflows
log distance	-0.040 (3.3)	-0.086 (7.29)
1st order contiguity	0.213 (4.9)	0.551 (13.0)
2nd order contiguity	0.201 (3.9)	0.540 (11.0)
3rd order contiguity	0.179 (3.3)	0.532 (10.0)
4th order contiguity	0.186 (3.3)	0.532 (9.6)
5th order contiguity	0.168 (3.3)	0.513 (8.6)
Regional dummies:		
South East	0.099 (6.6)	0.145 (9.9)
East Anglia	0.079 (3.9)	-0.090 (4.6)
London	0.611 (2.6)	0.537 (2.4)
South West	0.070 (6.0)	-0.062 (5.4)
West Midlands	0.073 (4.2)	--
South East / East Anglia	-0.096 (3.9)	--
South East / London	0.188 (5.8)	0.215 (6.8)
South East / South West	0.136 (7.2)	--
South East / East Midlands	0.084 (2.8)	--
East Anglia / East Midlands	0.106 (4.5)	-0.097 (4.2)
South West / West Midlands	--	-0.125 (4.9)
West Midlands / East Midlands	-0.114 (6.6)	-0.060 (3.6)
West Midlands / Wales	--	-0.097 (4.7)
East Midlands / Yorks.& Humbers.	--	-0.050 (3.0)
East Midlands / North West	0.065 (2.3)	--
Yorks.& Humbers. / North West	--	0.091 (5.4)
Yorks.& Humbers. / Cumbria	--	-0.161 (2.7)
Yorks.& Humbers. / Northern	--	-0.116 (4.4)
North West / Cumbria	--	-0.138 (2.6)
North West / Wales	--	-0.104 (3.4)
Cumbria / Scotland	--	-0.114 (2.2)
Adj. R^2	0.072	0.120

Keys: Absolute t-values in parentheses, distance cut-off is 120 km. Only fixed effects for adjacent regions considered.

Table 5. Spatial effects, regression with uniform AR(12) and groupwise heteroscedasticity

Dependent variable	*log unemployment outflows*			*log filled vacancies*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
log U_{t-1}	0.772* (0.0086)	0.792* (0.0081)	0.754* (0.0079)	-0.072* (0.0215)	-0.074* (0.0207)	-0.067* (0.0200)
log V_{t-1}	0.028* (0.0023)	0.026* (0.0023)	0.029* (0.0023)	0.447* (0.0061)	0.446* (0.0062)	0.448* (0.0061)
log $\Sigma\omega[c(1)]\times U_{t-1}$	-0.143* (0.0104)	--	--	0.155* (0.0270)	--	--
log $\Sigma\omega[c(1)]\times V_{t-1}$	0.039* (0.0039)	--	--	0.030* (0.0100)	--	--
log $\Sigma\omega[d]\times U_{t-1}$	--	-0.206* (0.0129)	--	--	0.215* (0.0333)	--
log $\Sigma\omega[d]\times V_{t-1}$	--	0.079* (0.0065)	--	--	0.052* (0.0167)	--
log $\Sigma I[0<d\leq 30]\times U_{t-1}$	--	--	-0.013* (0.0021)	--	--	-0.008 (0.0056)
log $\Sigma I[30<d\leq 60]\times U_{t-1}$	--	--	-0.110* (0.0095)	--	--	0.159* (0.0244)
log $\Sigma I[60<d\leq 90]\times U_{t-1}$	--	--	-0.004 (0.0021)	--	--	-0.019* (0.0058)
log $\Sigma I[90<d\leq 120]\times U_{t-1}$	--	--	0.003 (0.0022)	--	--	0.022* (0.0061)
log $\Sigma I[0<d\leq 30]\times V_{t-1}$	--	--	0.015* (0.0026)	--	--	0.008 (0.0068)
log $\Sigma I[30<d\leq 60]\times V_{t-1}$	--	--	0.026* (0.0039)	--	--	0.018 (0.0098)
log $\Sigma I[60<d\leq 90]\times V_{t-1}$	--	--	0.005 (0.0024)	--	--	0.015 (0.0065)
log $\Sigma I[90<d\leq 120]\times V_{t-1}$	--	--	-0.003 (0.0026)	--	--	-0.021* (0.0069)
adj. Rsq.	0.999	0.999	0.999	0.988	0.988	0.988
DW	1.94	1.94	1.95	1.88	1.88	1.88
RTS	0.696 (116*)	0.601 (439*)	0.702 (1039*)	0.560 (738*)	0.639 (791*)	0.555 (316*)
N	32154	32154	31898	32045	32045	31782

Keys: See Table 2. See text for further explanation. District and time fixed effects included.

Table 6. Spatial effects, regression with uniform AR(12) and groupwise heteroscedasticity, regional fixed effects

Dependent variable	*log unemployment outflows*			*log filled vacancies*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
log U_{t-1}	0.865* (0.0031)	0.868* (0.0030)	0.859* (0.0030)	0.366* (0.0079)	0.369* (0.0076)	0.357* (0.0077)
log V_{t-1}	0.053* (0.0022)	0.049* (0.0022)	0.056* (0.0022)	0.522* (0.0057)	0.523* (0.0058)	0.529* (0.0057)
log $\Sigma\omega[c(1)]\times U_{t-1}$	-0.069* (0.0040)	--	--	-0.048* (0.0105)	--	--
log $\Sigma\omega[c(1)]\times V_{t-1}$	0.079* (0.0036)	--	--	0.066* (0.0089)	--	--
log $\Sigma\omega[d]\times U_{t-1}$	--	-0.112* (0.0062)	--	--	-0.095* (0.160)	--
log $\Sigma\omega[d]\times V_{t-1}$	--	0.141* (0.0056)	--	--	0.089* (0.0140)	--
log $\Sigma I[0<d\leq 30]\times U_{t-1}$	--	--	-0.019* (0.0023)	--	--	-0.015* (0.0059)
log $\Sigma I[30<d\leq 60]\times U_{t-1}$	--	--	-0.034* (0.0034)	--	--	-0.005 (0.0082)
log $\Sigma I[60<d\leq 90]\times U_{t-1}$	--	--	0.0003 (0.0024)	--	--	-0.012 (0.0063)
log $\Sigma I[90<d\leq 120]\times U_{t-1}$	--	--	-0.003 (0.0025)	--	--	0.020* (0.0066)
log $\Sigma I[0<d\leq 30]\times V_{t-1}$	--	--	0.024* (0.0028)	--	--	0.023* (0.0071)
log $\Sigma I[30<d\leq 60]\times V_{t-1}$	--	--	0.053* (0.0037)	--	--	0.029* (0.0089)
log $\Sigma I[60<d\leq 90]\times V_{t-1}$	--	--	0.002 (0.0027)	--	--	0.010 (0.0066)
log $\Sigma I[90<d\leq 120]\times V_{t-1}$	--	--	0.0007 (0.0029)	--	--	-0.020* (0.0075)

continued...

Table 6. *continued*

Dependent variable	*log unemployment outflows*			*log filled vacancies*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
South East	0.041*	0.037*	0.045*	-0.205*	-0.191*	-0.204*
	(0.0067)	(0.0068)	(0.0067)	(0.0175)	(0.0179)	(0.0172)
East Anglia	0.064*	0.055*	0.073*	-0.110*	-0.119*	-0.102*
	(0.0095)	(0.0094)	(0.0096)	(0.0256)	(0.0255)	(0.0256)
London	0.079*	0.054	0.037	0.248*	0.252*	0.216*
	(0.0240)	(0.0242)	(0.0250)	(0.0453)	(0.0453)	(0.0445)
South West	0.010	0.002	0.017	-0.145*	-0.163*	-0.141*
	(0.0072)	(0.0074)	(0.0072)	(0.0181)	(0.0189)	(0.0179)
West Midlands	-0.071*	-0.078*	-0.076*	-0.126*	-0.121*	-0.126*
	(0.0077)	(0.0077)	(0.0076)	(0.0204)	(0.0210)	(0.0205)
East Midlands	-0.011	-0.025*	-0.021*	-0.015	-0.013	-0.007
	(0.0077)	(0.0079)	(0.0077)	(0.0211)	(0.0218)	(0.0212)
Yorkshire and	-0.009	-0.003	-0.008	-0.103*	-0.097*	-0.103*
Humberside	(0.0079)	(0.0079)	(0.0079)	(0.0207)	(0.0209)	(0.0207)
North West	0.035*	0.033*	0.023*	0.355*	0.366*	0.332*
	(0.0080)	(0.0084)	(0.0082)	(0.0196)	(0.0204)	(0.0197)
Cumbria	-0.033	-0.005	-0.016	0.162*	0.162*	0.190*
	(0.0159)	(0.0159)	(0.0162)	(0.0441)	(0.0442)	(0.0442)
Northern	0.021	0.043*	0.028*	0.055	0.063	0.053
	(0.0102)	(0.0102)	(0.0103)	(0.0279)	(0.0280)	(0.0279)
Wales	-0.092*	-0.093*	-0.089*	-0.077*	-0.088*	-0.072*
	(0.0081)	(0.0081)	(0.0080)	(0.0224)	(0.0226)	(0.0222)
Scotland	-0.034	-0.020	-0.013	-0.039	-0.051	-0.036
	--	--	--	--	--	--
metropol. dominant	-0.003	-0.006	-0.007	0.052*	0.049*	0.044
	(0.0071)	(0.0070)	(0.0071)	(0.0071)	(0.0180)	(0.0180)
metropol. subdom.	0.015*	0.011	0.008	-0.077*	-0.072*	-0.081*
	(0.0059)	(0.0056)	(0.0071)	(0.0154)	(0.0148)	(0.0145)
metropol. rural	-0.018	-0.021	-0.012	0.046	0.047	0.046
	(0.0101)	(0.0100)	(0.0101)	(0.0256)	(0.0256)	(0.0254)
freestanding urban	0.011	0.014	0.008	0.007	0.009	0.002
	(0.0057)	(0.0057)	(0.0057)	(0.0147)	(0.0147)	(0.0147)
freestanding rural	-0.005	0.002	0.003	-0.028	-0.033	-0.011
	--	--	--	--	--	--
Coastal district	-0.023*	-0.015	-0.012	0.039	0.021	0.052*
	(0.0062)	(0.0064)	(0.0059)	(0.0161)	(0.0162)	(0.0151)
Motorway	0.062*	0.057*	0.059*	0.043*	0.046*	0.037
	(0.0056)	(0.0056)	(0.0056)	(0.0151)	(0.0151)	(0.0149)
adj. Rsq.	0.982	0.983	0.983	0.930	0.930	0.934
DW	1.91	1.91	1.91	1.87	1.87	1.87
RTS	0.928	0.946	0.939	0.906	0.886	0.916
	(369*)	(109*)	(371*)	(92.7*)	(70.8*)	(114*)
N	32154	32154	31898	32045	32045	31782

Keys: See Table 2. See text for further explanation. Dummies for regions and "urbanity" were normalised such that coefficients provide the deviation from the average matching efficiency. The coefficient for

Scotland and freestanding rural TTWAs is calculated such that the respective group of coefficients adds up to one.